Distributed Learning

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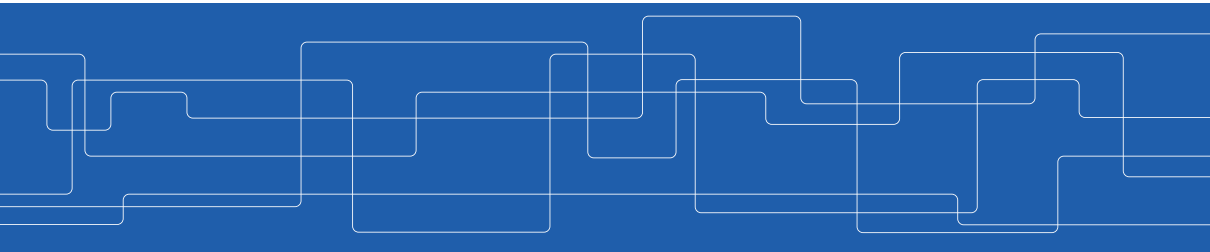
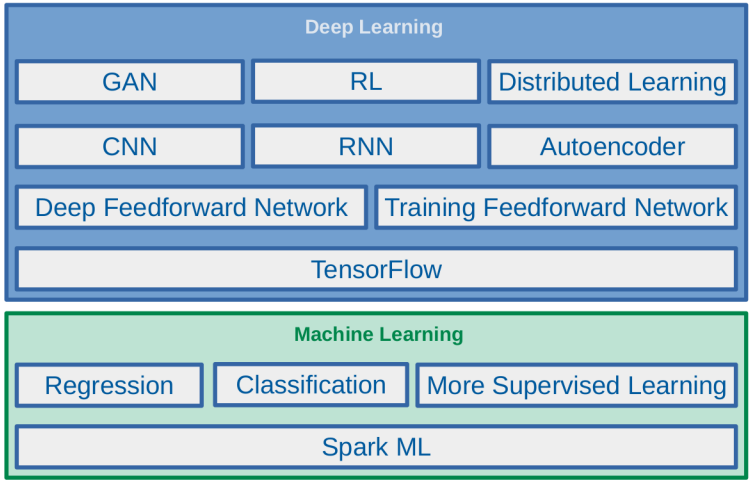
10/12/2019



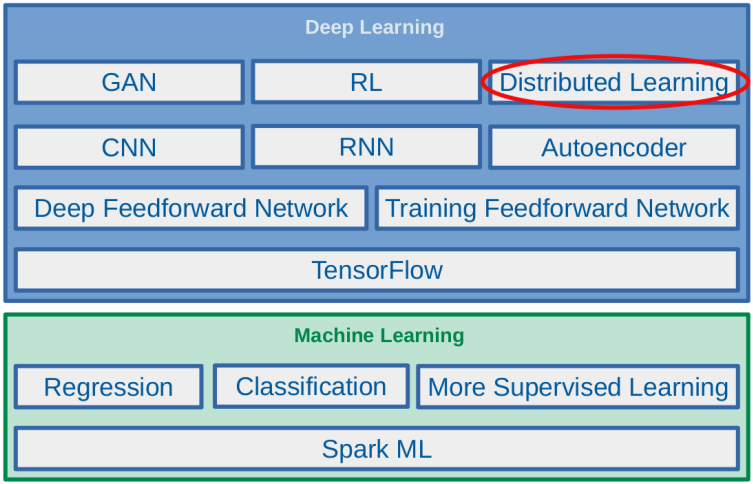
The Course Web Page

https://id2223kth.github.io

Where Are We?


Deep Learning
GAN
RL
Distributed Learning
CNN
RNN
Autoencoder
Deep Feedforward Network
Training Feedforward Network
TensorFlow
Machine Learning
Regression
Classification
More Supervised Learning
Spark ML

Where Are We?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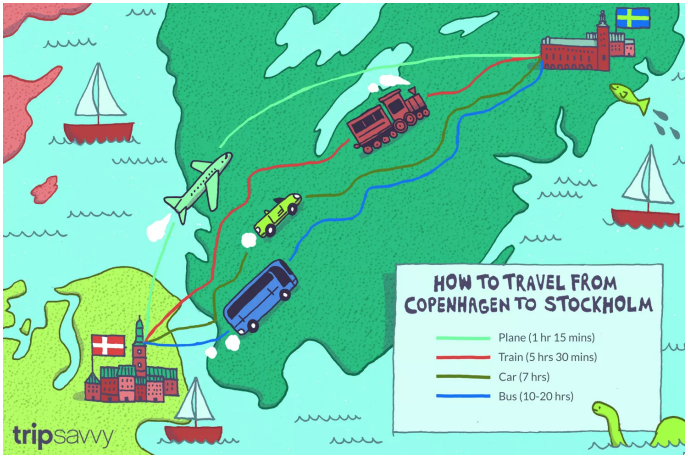
A few Words about CPU and GPU



[https://www.tripsavvy.com/how-to-get-from-copenhagen-to-stockholm-1626275]

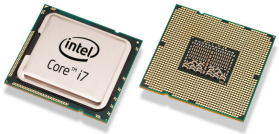
Ferrari or Truck?

Ferrari or Truck?

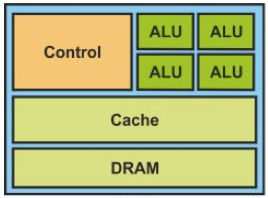
- Pick up your partner?

- Moving the furniture?

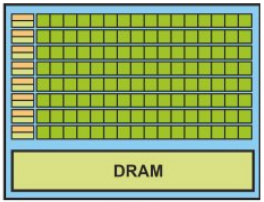
CPU vs GPU



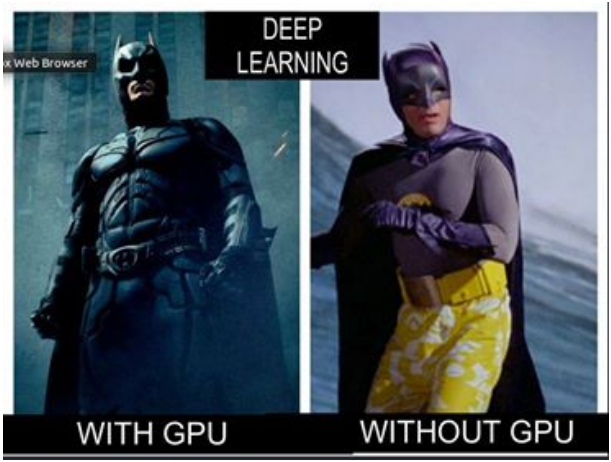
CPU vs GPU



CPU



GPU


x Web Browser
DEEP
LEARNING
WITH GPU
WITHOUT GPU

Do We Need GPU for Deep Learning?

- Which components of a DNN would require intense hardware resource?

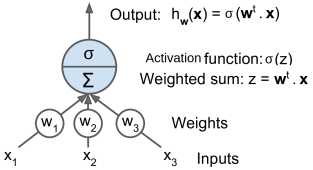
- A few candidates are:
  - Preprocessing input data
  - Training the model
  - Storing the trained model
  - Deployment of the model

- Which components of a DNN would require intense hardware resource?

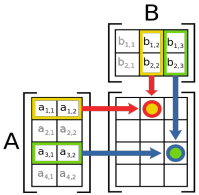
- A few candidates are:
  - Preprocessing input data
  - Training the model
  - Storing the trained model
  - Deployment of the model

Training a Model

- Forward pass: input is passed through the DNN and an output is generated.
- Backward pass: weights are updated on the basis of error we get in forward pass.

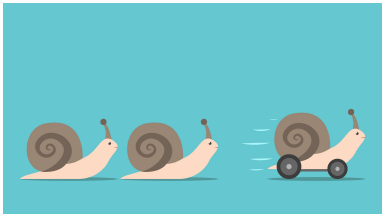


- Both of these operations are essentially matrix multiplications.



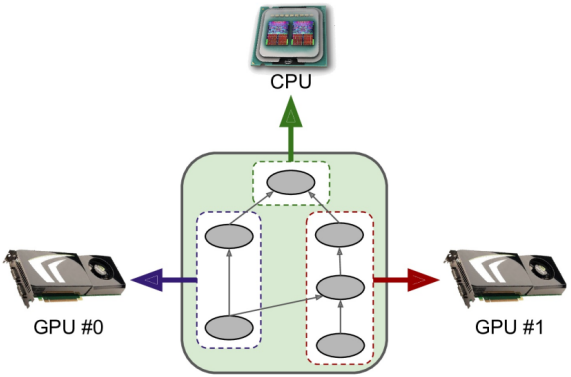
How to Train a Model Faster?

- The computationally intensive part of neural network is made up of multiple matrix multiplications.
- How can we make it faster?
- Do these operations at the same time, instead of doing it one after the other.
- This is in a nutshell why we use GPU instead of a CPU for training a neural network.



Placing Operations and Variables on Devices (1/4)

- For now, lets asume to run everything on a single machine.



Placing Operations and Variables on Devices (2/4)

- Place the data preprocessing operations on CPUs, and the NN operations on GPUs.
- Adding more CPU RAM to a machine is simple and cheap, whereas the GPU RAM is an expensive and limited resource.
  - If a variable is not needed in the next few training steps, it should probably be placed on the CPU (e.g., datasets generally belong on the CPU).
- GPUs usually have a fairly limited communication bandwidth, so it is important to avoid unnecessary data transfers in and out of the GPUs.

Placing Operations and Variables on Devices (3/4)

- By default, all variables/operations are placed on the first GPU: `/gpu:0`.
- Variables/operations that do not have a GPU kernel are placed on the CPU: `/cpu:0`.
- A kernel is a variable or operation's implementation for a specific data and device type.
  - For example, there is a GPU kernel for the `float32 tf.matmul()` operation, but there is no GPU kernel for `int32 tf.matmul()` (only a CPU kernel).

Placing Operations and Variables on Devices (4/4)

- TensorFlow automatically decides which device to execute an operation and copies tensors to that device.
- However, TensorFlow operations can be explicitly placed on specific devices using the `tf.device` context manager.

Manual Device Placement (1/3)

- Use `with tf.device` to create a device context.
- All the operations within that context will run on the same designated device.

```
tf.debugging.set_log_device_placement(True)

a = tf.constant([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
b = tf.constant([[1.0, 2.0], [3.0, 4.0], [5.0, 6.0]])
c = tf.matmul(a, b)
print(c)
```

```
Output:
Executing op MatMul in device /job:localhost/replica:0/task:0/device:GPU:0
tf.Tensor(
[[22. 28.]
 [49. 64.]], shape=(2, 2), dtype=float32)
```

Manual Device Placement (2/3)

```
tf.debugging.set_log_device_placement(True)

with tf.device('/cpu:0'):
  a = tf.constant([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
  b = tf.constant([[1.0, 2.0], [3.0, 4.0], [5.0, 6.0]])

c = tf.matmul(a, b)
print(c)
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```
Executing op MatMul in device /job:localhost/replica:0/task:0/device:GPU:0
tf.Tensor(
[[22. 28.]
 [49. 64.]], shape=(2, 2), dtype=float32)
```

- Here, `a` and `b` are assigned to `CPU:0`.
- Since a device was not explicitly specified for the `matmul` operation, it will be run on the default device `GPU:0`.

Manual Device Placement (3/3)

```
tf.debugging.set_log_device_placement(True)

with tf.device('/cpu:0'):
  a = tf.constant([[1.0, 2.0, 3.0], [4.0, 5.0, 6.0]])
  b = tf.constant([[1.0, 2.0], [3.0, 4.0], [5.0, 6.0]])
  c = tf.matmul(a, b)

print(c)
```

```
Executing op MatMul in device /job:localhost/replica:0/task:0/device:CPU:0
tf.Tensor(
[[22. 28.]
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```

Parallel Execution Across Multiple Devices

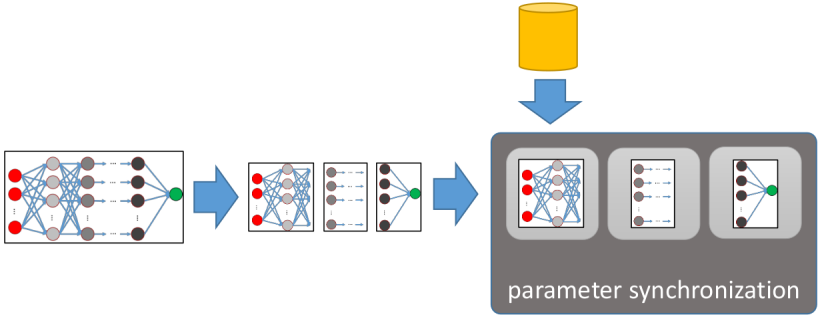
Parallelization

- Train large deep learning models with huge amounts of training data.
- Parallelization and distribution are essential.
- Two main approaches to training a single model across multiple devices:
  - Model parallelization
  - Data parallelization

Model Parallelization

Model Parallelization

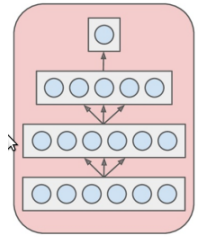
- The model is split across multiple devices.
- Depends on the architecture of the NN.



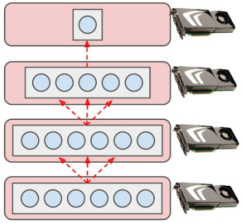
[Mayer, R. et al., arXiv:1903.11314, 2019]

Fully Connetected Model Parallelization (1/2)

- To place each layer on a different device.
- Not good: each layer needs to wait for the output of the previous layer before it can do anything.

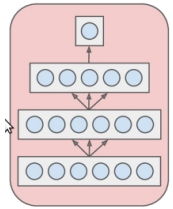


Fully connected neural network

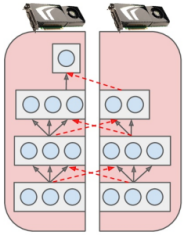

One layer per device

Fully Connetected Model Parallelization (2/2)

- Slice the model vertically.
  - E.g., the left half of each layer on one device, and the right part on another device.
- Slightly better: both halves of each layer can indeed work in parallel.
- Each half of the next layer requires the output of both halves: lot of cross-device communication.



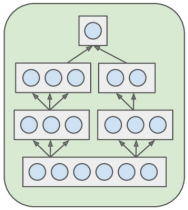
Fully connected neural network



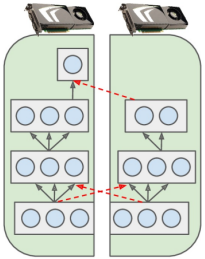
Vertical split

CNN Model Parallelization

- Some NN, such as CNN, contains layers that are only partially connected to the lower layers.
- Easier to distribute the model across devices in an efficient way.



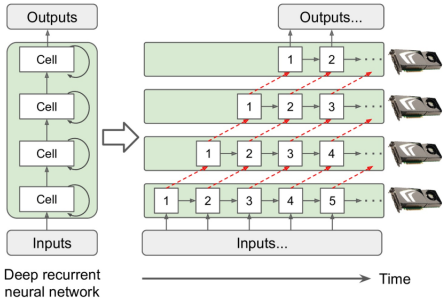
Partially connected neural network



Vertical split

RNN Model Parallelization

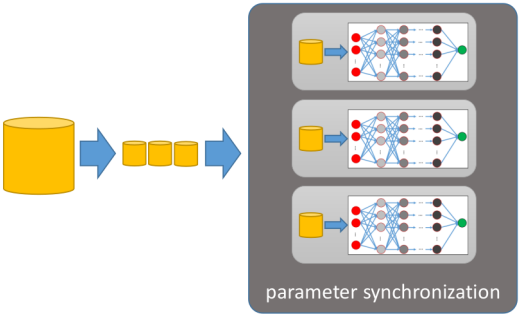
- Split the NN horizontally by placing each layer on a different device.
- At the first step, only one device will be active.
- At the second step, two will be active.
- While the first layer will be handling the second value, the second layer will be handling the output of the first layer for the first value.
- By the time the signal propagates to the output layer, all devices will be active simultaneously.



Data Parallelization

Data Parallelization (1/2)

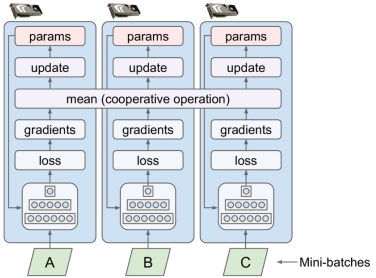
- Replicate a whole model on every device.
- Train all replicas simultaneously, using a different mini-batch for each.



[Mayer, R. et al., arXiv:1903.11314, 2019]

Data Parallelization (2/2)

1. Compute the gradient of the loss function using a mini-batch on each GPU.
2. Compute the mean of the gradients by inter-GPU communication.
3. Update the model.



Data Parallelization Design Issues

- System Architecture: how to synchronize the parameters
- Synchronization: when to synchronize the parameters

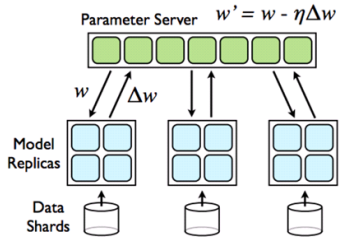
System Architecture

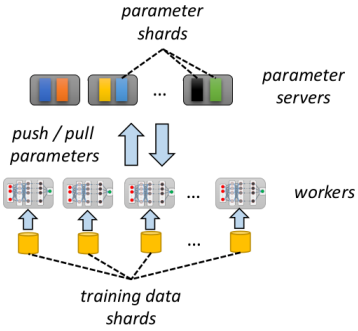
System Architecture - Centralized

- How to aggregate gradients (compute the mean of the gradients)?
- How the parameters of the different replicas are synchronized?

System Architecture - Centralized

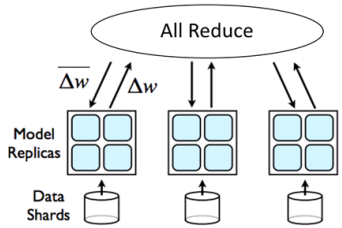
- Store the model parameters outside of the workers.
- Workers periodically report their computed parameters or parameter updates to a (set of) parameter server(s) (PSs).

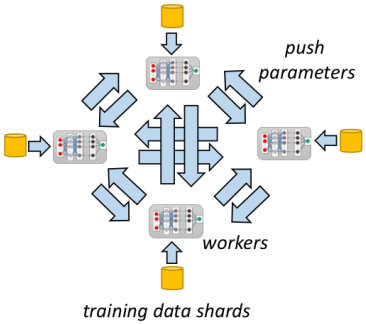




System Architecture - Decentralized

- Mirror all the model parameters across all workers (No PS).
- Workers exchange parameter updates directly via an allreduce operation.





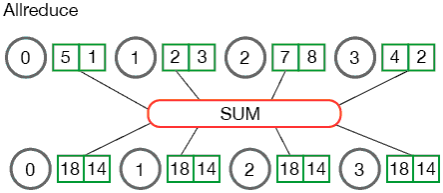
Reduce and AllReduce (1/2)

- Reduce: reducing a set of numbers into a smaller set of numbers via a function.
- E.g., `sum([1, 2, 3, 4, 5]) = 15`
- Reduce takes an array of input elements on each process and returns an array of output elements to the root process.

[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

Reduce and AllReduce (2/2)

- AllReduce stores reduced results across all processes rather than the root process.



[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

AllReduce Example

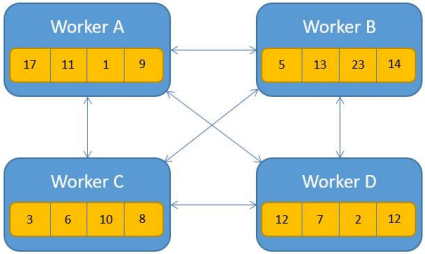
[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation

- All-to-all allreduce
- Master-worker allreduce
- Tree allreduce
- Round-robin allreduce
- Butterfly allreduce
- Ring allreduce

AllReduce Implementation - All-to-All AllReduce

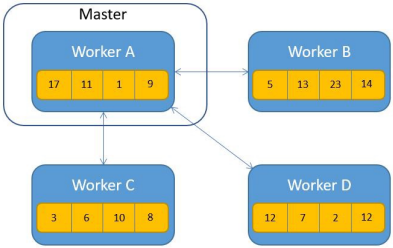
- Send the array of data to each other.
- Apply the reduction operation on each process.
- Too many unnecessary messages.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Master-Worker AllReduce

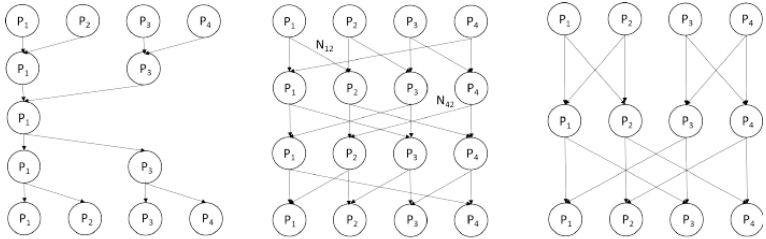
- Selecting one process as a master, gather all arrays into the master.
- Perform reduction operations locally in the master.
- Distribute the result to the other processes.
- The master becomes a bottleneck (not scalable).



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Other implementations

- Some try to minimize bandwidth.
- Some try to minimize latency.



(a) Tree AllReduce (b) Round-robin AllReduce (c) Butterfly AllReduce

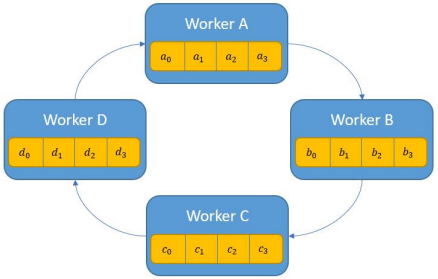
[Zhao H. et al., arXiv:1312.3020, 2013]

AllReduce Implementation - Ring-AllReduce (1/6)

- The Ring-Allreduce has two phases:
  1. First, the share-reduce phase
  2. Then, the share-only phase

AllReduce Implementation - Ring-AllReduce (2/6)

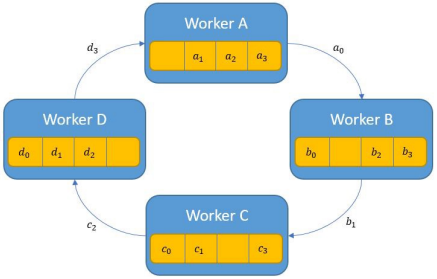
- In the share-reduce phase, each process `p` sends data to the process `(p+1) % m`
  - `m` is the number of processes, and `%` is the modulo operator.
- The array of data on each process is divided to `m` chunks (`m=4` here).
- Each one of these chunks will be indexed by `i` going forward.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (3/6)

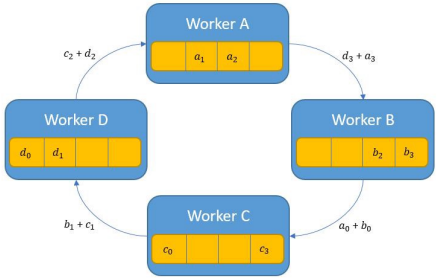
- In the first share-reduce step, process `A` sends a_0 to process `B`.
- Process `B` sends b_1 to process `C`, etc.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (4/6)

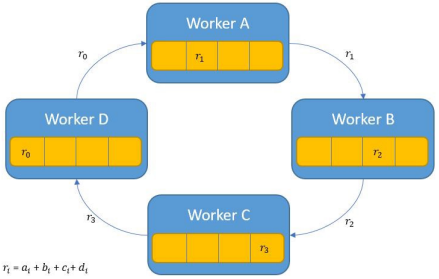
- When each process receives the data from the previous process, it applies the reduce operator (e.g., sum or mean)
  - The reduce operator should be associative and commutative.
- It then proceeds to send it to the next process in the ring.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (5/6)

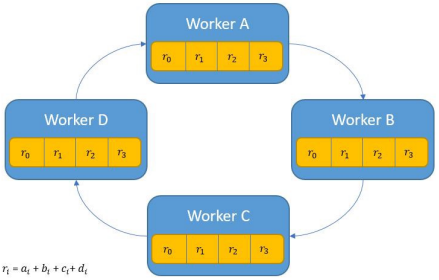
- The share-reduce phase finishes when each process holds the complete reduction of chunk `i`.
- At this point each process holds a part of the end result.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (6/6)

- The share-only step is the same process of sharing the data in a ring-like fashion without applying the reduce operation.
- This consolidates the result of each chunk in every process.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

Master-Worker AllReduce vs. Ring-AllReduce

- N: number of elements, m: number of processes
- Master-Worker AllReduce
  - First each process sends N elements to the master: $N \times (m-1)$ messages.
  - Then the master sends the results back to the process: another $N \times (m-1)$ messages.
  - Total network traffic is $2(N \times (m-1))$, which is proportional to m.
- Ring-AllReduce
  - In the share-reduce step each process sends $\frac{N}{m}$ elements, and it does it $m-1$ times: $\frac{N}{m} \times (m-1)$ messages.
  - On the share-only step, each process sends the result for the chunk it calculated: another $\frac{N}{m} \times (m-1)$ messages.
  - Total network traffic is $2(\frac{N}{m} \times (m-1))$.

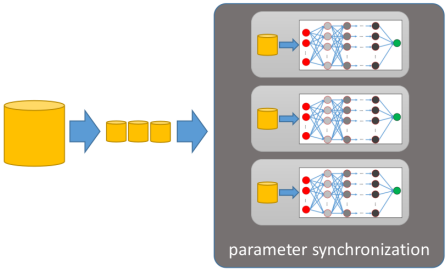
Synchronization

Synchronization

- When to synchronize the parameters among the parallel workers?

Synchronization - Synchronous

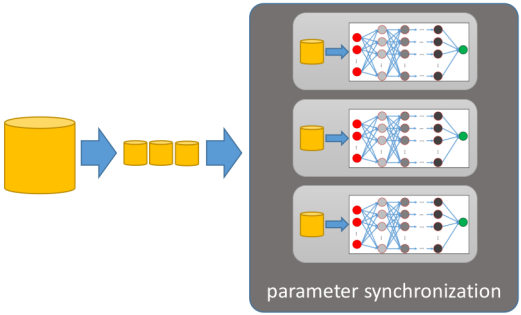
- After each iteration (processing of a mini-batch), the workers synchronize their parameter updates.
  - Easy to reason about the model convergence.
  - The training process prone to the straggler problem, where the slowest worker slows down all the others.



[Mayer, R. et al., arXiv:1903.11314, 2019]

Synchronization - Asynchronous

- Workers update their model independently from each other.
  - A worker may train on stale (delayed) parameters.
  - This makes it hard to mathematically reason about the model convergence.
  - It provides the workers flexibility in their training process, completely avoiding all straggler problems.



[Mayer, R. et al., arXiv:1903.11314, 2019]

Data Parallelization in TensorFlow

TensorFlow Distribution Strategies

- `tf.distribute.Strategy` is a TensorFlow API to distribute training.
- Supports both parameter server and allreduce models.

Single Server

Single Server Training - MirroredStrategy (1/2)

- Synchronous distribute training training on multiple GPUs on one machine.
- One replica per GPU.
- The parameters of the model are mirrored across all the replicas.
- These parameters are kept in sync with each other by applying identical updates.
- The parameters updates are communicated using allreduce algorithms.

```
mirrored_strategy = tf.distribute.MirroredStrategy()

# to use only some of the GPUs on your machine
mirrored_strategy = tf.distribute.MirroredStrategy(devices=["/gpu:0", "/gpu:1"])
```

Single Server Training - MirroredStrategy (2/2)

- There are different implementation of allreduce.
- You can override the cross GPU communication:
  - `tf.distribute.NcclAllReduce` (the default)
  - `tf.distribute.ReductionToOneDevice`
  - `tf.distribute.HierarchicalCopyAllReduce`

```
mirrored_strategy = tf.distribute.MirroredStrategy(
    cross_device_ops=tf.distribute.HierarchicalCopyAllReduce())
```

Single Server Training - CentralStorageStrategy

- Parameters are not mirrored, instead they are placed on the CPU.
- Operations are replicated across all local GPUs.
- Does synchronous training.

```
central_storage_strategy = tf.distribute.experimental.CentralStorageStrategy()
```

Single Server Trainings - Example

- Creat a strategy, e.g., `MirroredStrategy` or `CentralStorageStrategy`.
- Call its `scope()` method to get a distribution context.
- Wrap the creation and compilation of the model inside that context.
- Call the model's `fit()` and `predict()` method normally (outside the context).

```
distribution = tf.distribute.MirroredStrategy()

with distribution.scope():
    model = keras.models.Sequential([...])
    model.compile(...)

model.fit(...)
model.predict(...)
```

Multi Servers

Multi Servers Trainings - MultiWorkerMirroredStrategy (1/2)

- Very similar to `MirroredStrategy`.
- Synchronous distributed training across multiple workers, each with potentially multiple GPUs.
- Makes copies of all parameters of the model on each device across all workers.

```
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
```

Multi Servers Trainings - MultiWorkerMirroredStrategy (2/2)

- Two different implementations:
  - `CollectiveCommunication.RING` (ring-based implementation)
  - `CollectiveCommunication.NCCL` (Nvidia's NCCL implementation)
- `CollectiveCommunication.AUTO` defers the choice to the runtime.
- The best choice of collective implementation depends upon the number and kind of GPUs, and the network interconnect in the cluster.

```
# ring-based collectives
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy(
    tf.distribute.experimental.CollectiveCommunication.RING)
```

Multi Servers Trainings - ParameterServerStrategy

- Supports parameter servers training on multiple machines.
- Some machines are designated as workers and some as parameter servers.
- Each parameter of the model is placed on one parameter server.
- Computation is replicated across all GPUs of all the workers.

```
ps_strategy = tf.distribute.experimental.ParameterServerStrategy()
```

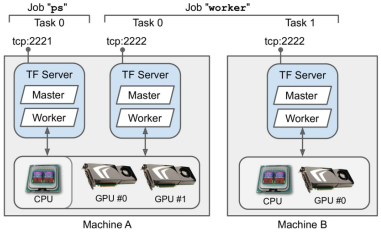
Multi Servers Trainings - More Details

- A TensorFlow cluster is a group of TensorFlow processes running in parallel.
- Each TF process (a.k.a task) in the cluster has a type:
  - Worker: performs computations, usually on a machine with one or more GPUs.
  - Parameter Server (ps): keeps track of parameters values, it is usually on a CPU-only machine.
- The set of tasks that share the same type is often called a job. For example, the worker job is the set of all workers.

Multi Servers Trainings - Example (1/3)

- Assume a cluster with 3 tasks (2 workers and 1 parameter server).

```
cluster_spec = tf.train.ClusterSpec({
    "worker": [
        "machine-a.example.com:2222", # /job:worker/task:0
        "machine-b.example.com:2222"  # /job:worker/task:1
    ],
    "ps": ["machine-a.example.com:2221"] # /job:ps/task:0
})
```



Multi Servers Trainings - Example (2/3)

- To start a task, you must give it the cluster spec and define its type and index (ID), e.g., worker 0.

```
ps0 = tf.distribute.Server(cluster_spec, job_name="ps", task_index=0)
```

```
worker0 = tf.distribute.Server(cluster_spec, job_name="worker", task_index=0)
```

```
worker1 = tf.distribute.Server(cluster_spec, job_name="worker", task_index=1)
```

Multi Servers Trainings - Example (3/3)

- Alternative way to specify a cluster spec is to use the `TF_CONFIG` environment variable before starting the program.
- For example to run worker 1:

```
distribution = tf.distribute.experimental.ParameterServerStrategy()

os.environ["TF_CONFIG"] = json.dumps({
   "cluster": {
     "worker": ["machine-a.example.com:2222", "machine-b.example.com:2222"],
     "ps": ["machine-a.example.com:2221"]},
   "task": {"type": "worker", "index": 1}
})

with distribution.scope():
    model = keras.models.Sequential([...])
    model.compile(...)

model.fit(...)
```

Communication Overhead

Communication Overhead in Data Parallelization

- Synchronizing the model replicas in data-parallel training requires communication between workers (in allreduce)
- Between workers and parameter servers (in the centralized architecture).
- Such communication can easily become the bottleneck of the overall training process.

Approaches for Communication Efficiency

- Reducing the model precision
- Compressing the model updates
- Improving the communication scheduling

Reducing the Model Precision

- Reduce the precision of the parameters' data types, e.g., from double precision to single floating point.
- It saves communication bandwidth when parameter updates need to be transferred over the network.
- It reduces the model size, which can be useful when the model is deployed on resource-constrained hardware such as GPUs.

Compressing the Model Updates

- The model updates communicated between workers and between workers and parameter servers can be compressed.
- Gradient quantization: reducing the number of bits per gradient.
- Gradient sparsification: communicating only important gradients that have a significant value.

Improving the Communication Scheduling

- Communication patterns in data-parallel are typically bursty, especially in synchronous systems.
  - All workers may share their updated parameters at the same time with their peer workers or parameter servers.
- To prevent that the network bandwidth is exceeded and communication is delayed, the communication of the different workers can be scheduled such that it does not overlap.
  - Prioritize specific messages over others.

Summary

Summary

- CPU vs. GPU
- Parallelization
- Model-parallel
- Data-parallel
  - Parameter server vs. AllReduce
  - Synchronized vs. asynchronoused
- Communication challenges

Reference

- Aurélien Géron, Hands-On Machine Learning (Ch. 19)
- Mayer, R. et al., “Scalable Deep Learning on Distributed Infrastructures: Challenges, Techniques and Tools”, 2019.

Questions?